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# A Novel Approach for Detection, Segmentation, and Classification of Brain Tumors in MRI Images Using Neural Network and Special C Means Fuzzy Clustering Techniques

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**Abstract:**

Brain tumors present a significant health challenge globally, necessitating advanced techniques for accurate detection, segmentation, and classification. This paper presents a comprehensive study focused on the development and evaluation of innovative methodologies for brain tumor analysis using medical imaging data. The primary objective of this research is to enhance the accuracy and efficiency of brain tumor detection, segmentation, and classification processes. To achieve this goal, a multi-step approach is proposed, integrating various computational techniques and machine learning algorithms. First, the study explores novel methods for preprocessing medical imaging data to enhance image quality and reduce noise artifacts. This preprocessing step plays a crucial role in improving the subsequent analysis stages' accuracy and reliability. Next, a robust tumor detection algorithm is developed, leveraging advanced image processing techniques and deep learning models. The proposed algorithm effectively identifies tumor regions within brain images with high accuracy and minimal false positives. Following tumor detection, a segmentation framework is introduced to precisely delineate tumor boundaries from surrounding healthy tissues. The segmentation algorithm combines traditional image processing methods with state-of-the-art deep learning architectures to achieve accurate and efficient tumor delineation.

In this paper, we proposed three novel methods for automatic detection, classification, and segmentation of brain tumors. Comprehensive experiments are conducted on the BRATS dataset and show that the proposed model

obtains competitive results. The parameters under study are Accuracy rate, Specificity, and Sensitivity.

First approach focuses on classifying cancerous and non-cancerous brain tumors in MRI scans. The system first reads the images and employs a novel fusion method to combine information from various modalities (Flair, T1, T1C, T2) for a more comprehensive picture. This enhances the accuracy of tumor characterization. Following this fusion, the images undergo preprocessing, feature extraction, and classification. The preprocessing stage involves grayscale conversion, binarization, wavelet analysis, and region-of-interest (ROI) calculation. Finally, a robust Neural Network (NN) classification method effectively differentiates cancerous and non-cancerous brain tissue. Performance is evaluated by metrics like accuracy, sensitivity, and specificity. Compared to existing methods, this research system demonstrates superior results, achieving a classification accuracy of 96.61%, sensitivity of 96.66%, and specificity of 96.55%. The Second approach combines Backpropagation Neural Networks (BPNN) with Spatial Fuzzy C-Means (SFCM) clustering for brain tumor analysis. The BPNN classifies brains into normal, benign (non-cancerous abnormality), or malignant (cancerous) categories. SFCM helps pinpoint the exact tumor location and size within the MRI scan through segmentation. A dual-tree complex wavelet transform is employed to extract image features efficiently. This method achieved exceptional results: 99.77% classification accuracy, 99.87% sensitivity (correctly identifying tumors), and 98.69% specificity (correctly identifying healthy tissue). Additionally, the over 90% precision demonstrates the effectiveness of this technique in feature extraction and classification. The experiments demonstrate that BPNN-SFCM successfully segment, and extracts brain tumors from MRI scans. The overall accuracy of BPNN-SFCM is better as compared to other proposed methods and existing methods.

**Keywords**:. Novel Approach, Brain Tumors, MRI, Neural Network, Fuzzy Clustering Techniques.

## 1. INTRODUCTION

Cells are the fundamental components of all living organisms. Tissues are formed by groups of comparable cells that have the same purpose. Normal cells undergo self-destruction or are replaced by new cells when they become damaged or reach the end of their lifespan. However, there are instances where the production of new cells is unnecessary or when normal cells fail to undergo self-destruction when they are worn out. In this scenario, these additional cells accumulate and give rise to an aggregation of tissue known as a tumor, which proliferates without restraint. Figure 1 illustrates the distinction between healthy cells and cancerous cells.

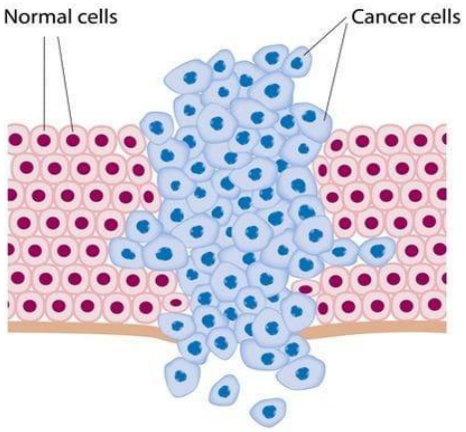



Figure 1 Normal Cells and Cancer Cells

(Source: https://www.cancerfoundation.org.au/what-is-cancer-.html)

### 1.1 Types of Brain Tumor

There are two basic forms of brain tumors: benign and malignant[1]

**a. Benign Brain Tumors**

Characteristics: Benign brain tumors are non-cancerous growths. They have clearly defined borders, grow slowly, and usually do not spread to surrounding tissues. However, their location can still cause significant problems depending on the area of the brain they affect.

Treatment and Prognosis: Surgical removal is often effective, and these tumors have a lower risk of recurrence. Their impact on health depends on their size and location, as even benign tumors can cause serious symptoms if they press against vital brain structures.

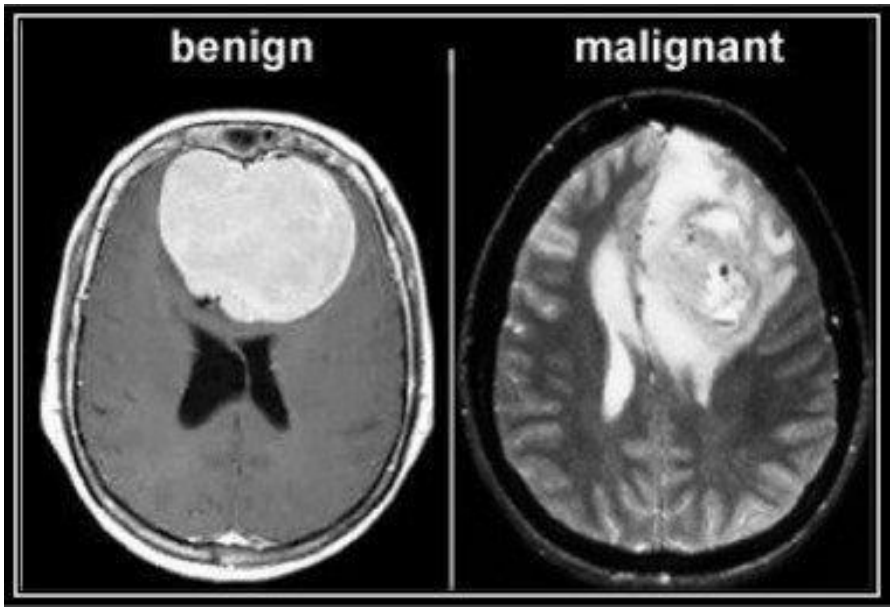



Figure 2 Benign and Malignant Brain Tumor

**b. Malignant Brain Tumors**

Characteristics: Malignant brain tumors are cancerous and more aggressive. They grow rapidly, lack clear borders, and can attack surrounding brain tissue. This makes them more difficult to completely remove surgically[2].

Treatment usually consists of a mix of surgery, radiation therapy, and chemotherapy. The outlook for malignant brain tumors varies significantly based on the tumor kind, location, and the patient's general condition.

Malignant tumors often have a higher risk of recurrence and can spread to other parts of the brain or spinal cord. Figure 2 represents the Benign and Malignant types of brain tumors.

**c. Other Types**

Brain tumors are categorized depending on their biological origin and their specific location inside the brain. Common types include:

**i. Gliomas:** These originate in the glial cells and are one of the most common types of brain tumors. Gliomas can be either benign or malignant and are categorized into several subtypes, including astrocytomas, oligodendrogliomas, and glioblastomas, the latter being highly malignant.

**ii. Meningiomas:** Meningiomas are tumors that develop from the meninges, the layers of tissue covering the brain and spinal cord. These tumors are typically slow-growing and often benign, meaning they are not cancerous. Meningiomas account for about 30% of all primary brain tumors. They can occur in various parts of the brain and spinal cord, and their location determines the symptoms and potential complications.

**iii. Schwannomas:** Benign tumors that affect the Schwann cells, which form the protective covering of the peripheral nerves. Schwannomas are tumors that arise from Schwann cells, which are the cells that produce the insulating myelin sheath covering peripheral nerves. These tumors are typically benign, slow-growing, and are also known as neurilemmomas.

**iv. Pituitary adenomas:** Pituitary gland tumors can impact hormone levels in the body. These are usually benign.

**v. Medulloblastomas**: These are malignant tumors that originate in the cerebellum. They are more common in children.

**1.2 Magnetic Resonance Images**

Utilizing a diverse range of strategies and Imaging modalities including MRI, Positron Emission Tomography (PET), and Computed Tomography (CT) scans can aid in promptly identifying any abnormal changes in brain structures and tissues. MRI images are commonly utilized for the identification and categorization of brain malignancies.

Magnetic Resonance Imaging (MRI) is a method used to visualize intricate aspects of human anatomy and tissue. The image displayed is grayscale, allowing for clear observation

of tissue texture changes. It is superior to Computed Tomography (CT) in visualizing brain tumors and malignant areas[3][4].

MRI images are commonly utilized in brain tumor diagnosis algorithms due to their ease of acquisition and manipulation. They are available in many types categorized by contrast. Treatment is determined by characteristics such as the form, size, kind, grade, and location of the cancer.

The factors can vary greatly depending on the patient's health. Therefore, precise identification and categorization of brain tumors are essential for appropriate treatment. Magnetic resonance imaging (MRI) is a radiological technique used to generate visual depictions of the body's anatomical structure and physiological activities[5]. Figure 1.5 represents the MRI Scanner Cutaway.

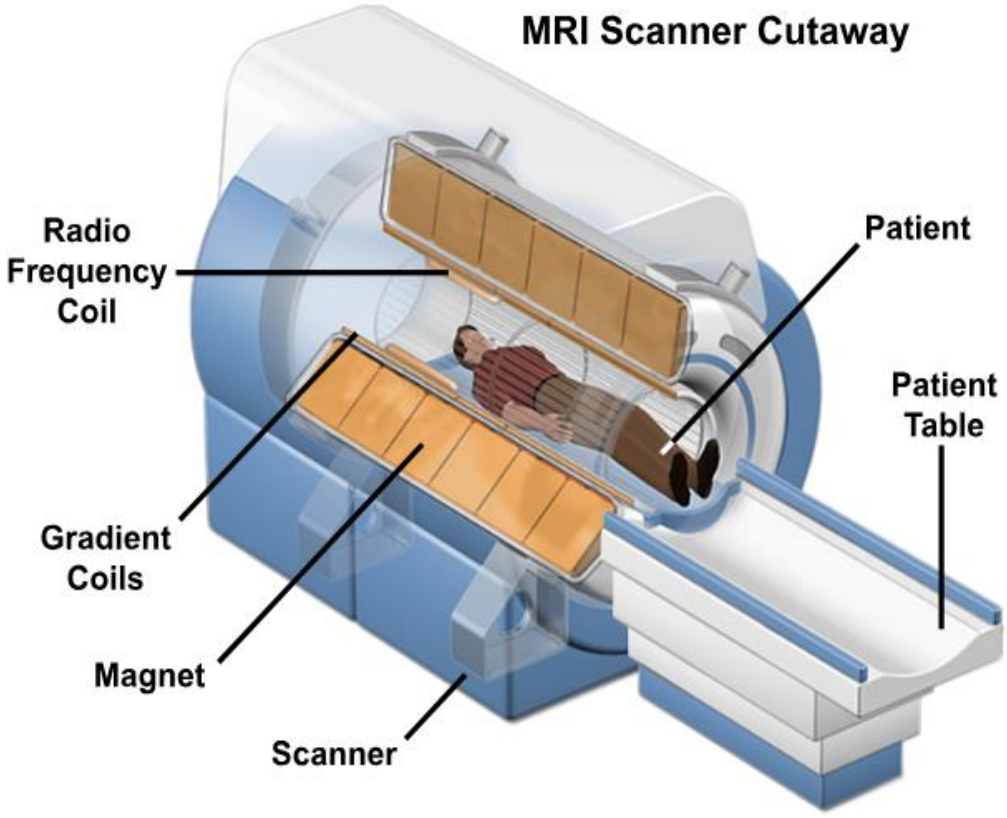



Figure 3 MRI Scanner Cutaway

**1.3 Statistics:**

The data from 2019 reveals a significant global burden of brain cancer, with 347,992 new cases reported worldwide. Gender disparities are evident, as 54% of these cases occurred in males, while 46% affected females.

Tragically, there were 246,253 fatalities attributed to brain cancer during the same year, with 56% being males and 44% females. Examining regional variations, the Western Pacific

Region stood out with the highest incidence of newly registered cases (34.5% of the total) and deaths (30.7% of the total) across both sexes.

In contrast, the African region reported the lowest numbers, accounting for only 2.3% of newly registered cases and 2.4% of deaths. Analyzing the age-standardized rates (ASRs), the global incidence of brain cancer in 2019 was 12 per 100,000 in men and 3.6 per 100,000 in females. Similarly, the Age Standardized Rate (ASR) for death was 3.9 per 100,000 in males and 2.6 per 100,000 in females.

Across all World Health Organization (WHO) regions, men consistently faced higher rates of both incidence and mortality from brain cancer compared to women. These statistics underscore the pressing need for continued research, awareness, and support to address the global impact of brain cancer. Efforts to understand the underlying factors contributing to gender disparities and regional variations are crucial in developing effective prevention, diagnosis, and treatment strategies for this devastating disease[6]. In 2020, brain tumors were ranked tenth among the most common tumors seen among Indians. The International Association of Cancer Registries (IARC) reported over 28,000 cases of brain tumors reported in India each year, and more than 24,000 people reportedly die due to brain tumors annually.

Table 1 represents the Incidence and Mortality rates of brain cancer in 2019, categorized by WHO regions and genders.

Table 1 Incidence and mortality rates of brain cancer in 2019, categorized by WHO regions and genders.

| Region | NEW CASES | | | | DEATHS | | | |
|---|---|---|---|---|---|---|---|---|
| | Male | | Female | | Male | | Female | |
| | Number | % | Number | % | Number | % | Number | % |
| Western Pacific Region | 60748 | 32.4 | 59452 | 37 | 42433 | 30.6 | 33273 | 30.9 |
| European Region | 45744 | 24.4 | 37688 | 23.5 | 33385 | 24.1 | 25920 | 24.1 |
| Region of the Americas | 32446 | 17.3 | 27054 | 16.9 | 24749 | 17.9 | 19825 | 18.4 |
| South East Asia Region | 23729 | 12.7 | 27054 | 16.9 | 20260 | 14.6 | 16658 | 15.5 |
| Eastern Mediterranean Region | 15779 | 8.4 | 10024 | 6.2 | 10582 | 7.6 | 6638 | 6.2 |
| African Region | 8461 | 4.5 | 6127 | 3.8 | 6792 | 4.9 | 4990 | 4.6 |
| Global | 187491 | 100 | 160501 | 100 | 138605 | 100.0 | 107648 | 100.0 |

The digital image processing can play an important role in the medical side of identifying diseases and tumors. A digital image can be collected of a fixed number of elements known as image elements or pixels, every one of which contains an intensity value and exacting position. In the medical area, MRI can be mostly utilized for finding the idea of details in the body's inner structure.

In Image processing techniques for brain tumor classification and segmentation involve a series of computational steps designed to analyze MRI images, identify the presence of

tumors, classify their type, and delineate their boundaries from healthy brain tissue[7]. This process typically involves the following key steps which are depicted in figure 4:

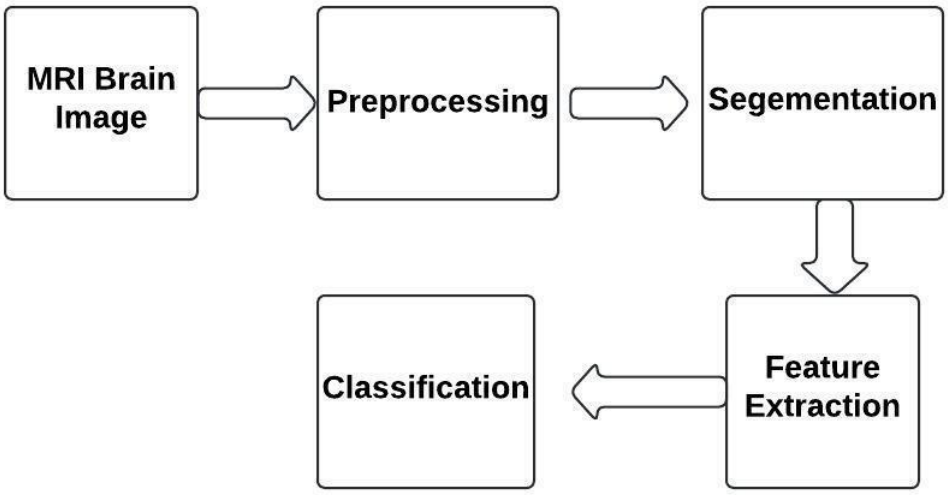



Figure 4 Image Processing Steps

## 2. LITERATURE REVIEW

This SECTION summarizes prior brain tumor detection, segmentation, and classification research. It gives an in-depth overview of the subject area and facts to support the research in this paper

The summary of in-depth study is presented in a detailed table, which explains the most important insights and consequences of the approaches that were examined in the examination of brain tumors. A concise summary of the literature review is shown in Table 2 Using the BRATS dataset, every technique is tested and evaluated. Through this snapper, we aim to contribute to the collective understanding of effective methodologies in the critical field of brain tumor research.

Table 2 Literature Review of Brain Tumor Classification and Segmentation Techniques

| Sr No | Title / Author / Year / Publication | Method | Remarks |
|---|---|---|---|
| 1 | "Brain tumor segmentation in MR images using a sparse constrained level set algorithm", Xiaoliang Lei Et al., 2020, Elsevier[8] | Deep Learning Models | Need a large amount of data to avoid overfitting.<br>Difficult to apply to another dataset<br>Accuracy - 96.2% |
| 2 | "Microscopic brain tumor detection and classification using 3D CNN and feature selection architecture", Amjad Rehman, 2019, Wiley[9] | Support Vector Machine, K- Nearest Neighbour, Neural Network | When employing this architecture, the tumor was correctly detected in MRI scans with low contrast; however, the accuracy of the identification was not as high when the images had low contrast and irrelevant features. |

| | | | |
|---|---|---|---|
| | | | Accuracy - 98.32 |
| 3 | "Detection of Brain Tumor and Extraction of Features in MRI Images Using K-means Clustering and Morphological Operations", Z. Zulkoffli 2019, IEEE[10] | Threshold-based, Morphological operations and Kmeans | 1. The problem with thresholding is that it does not work well if the difference in intensity is very low. It may not accurately capture the region of interest.<br>2. Another problem is that if there is more than one region that is not connected and has different intensities, one of them will not be detected<br>Accuracy - 91.65% |
| 4 | "Automated tissue segmentation of MR brain images in the presence of white matter lesions", Sergi Valverde , 2016, Medical Image Analysis[11] | Multiple Sclerosis SEGmentation Pipeline(MSSEG) | Method has been tested only with Flair MRI Images |

### 2.1 Findings from the Literature Review

The objective of medical image processing is to improve the current tools used in medical imaging by automating them, reducing the need for manual intervention by medical professionals. Detecting brain tumors involves isolating aberrant tissues from normal brain tissues. Computer-aided diagnosis (CAD) systems face increased difficulty due to the variety in tumor regions, sizes, and shapes. Various brain tumor detection algorithms are reviewed, highlighting the challenges and advantages faced to identify different forms of brain tumors. Prior knowledge of these techniques helps us to focus on developing sophisticated algorithms for medical image processing. Existing brain tumor classification and segmentation techniques have made significant advancements, but they also face certain limitations and drawbacks such as low accuracy, segmentation error, computational complexity, and computation time.

- Many classification models are trained and evaluated on specific datasets, which may limit their generalizability to diverse patient populations or different imaging modalities. Integrating information from various imaging modalities is still challenging.
- Further, Fuzzy clustering methods may not handle noise and outliers well and may give uncertain results due to the same.
- For large datasets or high-dimensional feature spaces, popular algorithms like KNN and Support Vector Machine can become inefficient and slow, making them impractical for real-time or large-scale applications.
- Modifying the pixel intensity in methods such as Random Forest may impact the ultimate segmentation accuracy.

The main objective of this work is to overcome these drawbacks and to develop a simple, robust, and efficient algorithm for the segmentation of brain tumor images.

## 3. PROPOSED METHODOLOGY

Two unique methods are offered, each of which yields enhanced outcomes compared to the systems that are now in use, as described in the following table 3.

Table 3: Methods used for pre-processing, Feature Extraction, Classification, and Segmentation in Proposed Research

| Methods Implemented | Pre-processing | Feature Extraction | Classification | Segmentation |
|---|---|---|---|---|
| "MRI Brain Tumor Image Classification Using Morphological Operations and NN Algorithm" | Median Filtering | DWT<br>Local Binary Pattern (LBP)<br>Grey Level Run Length Matrix (GLRLM) | BPNN Classifier | Advanced Active contour-based segmentation |
| "Brain Tumor Classification and Segmentation using DTCW Transform, Back Propagation NN, and Spatial Fuzzy C-Means Clustering" | Median Filtering | - "Dual-Tree Complex Wavelength Transform (DT CWT)"<br>- "Gray-Level Co-Occurrence Matrix (GLCM)" | BPNN Classifier | Special C Means Fuzzy Clustering for segmentation |

The primary goal of this work is to use a novel clustering method to segment the tumor portion of the affected MRI. Furthermore, even though many scholars have studied the diagnosis of brain tumors, the accuracy-based performance metric in diagnosis results is low. As a result, three novel methods are proposed in this research with improved results compared to existing systems, as depicted in Table 3.

### 3.1 MRI Brain Tumor Image Classification using Morphological Operations and Neural Network Algorithm (MONN)

Figure 5 provides a detailed depiction of the block diagram for the MONN model. This diagram is structured into six distinct stages: input, fusion, pre-processing, segmentation, feature extraction, and classification. Each stage plays a crucial role in the overall functioning of the model. The input stage begins with the collection of raw data, which is then combined in the fusion stage. Following this, the pre-processing stage prepares the data for further analysis. The segmentation stage extract the tumor part from the entire MRI image. In the feature extraction stage, relevant attributes are identified and isolated. Finally, the classification stage categorizes the image into normal or abnormal brain.

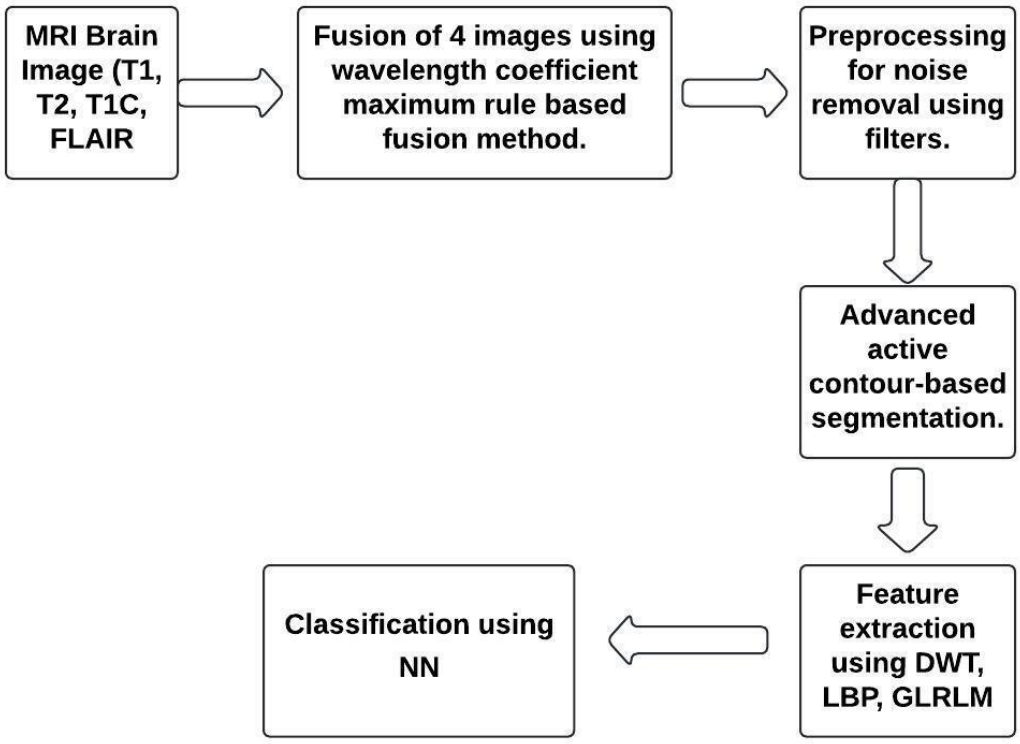



Figure 5 Block diagram of MONN Model

The steps involved in MRI Brain Tumor Image Classification using Morphological Operations and Neural Network are illustrated in the below algorithm.

**Algorithm for MONN Model**[26]

*Step 1: Input - As input, MRI samples are provided.*

*Step 2: Fusion – Fusion of 4 images using wavelength coefficient maximum rule-based fusion method*

*Step 3: Preprocessing– Pre-processing, Skull-stripping, or brain extraction, is the process of eliminating non-brain tissue signals from magnetic resonance imaging (MRI) data for noise removal*

*Step 4: Segmentation - Advanced Active Contour Based Segmentation*

*Step 5: Feature Extraction - Feature extraction using DWT, LBP, GLRLM*

*Step 6: Classification - Classification using Back Propagation Neural Network*

*Output: Segmented Tumor Image*

### 3.1.1 Fusion and pre-processing

- Firstly, examine the Brain Tumor Image (MRI) T1C and T2 Image series. Obtain the S1 picture by fusing the T1C and T2 MRI brain imaging series using wavelet transformation (DWT) using the maximum procedure and display it[27].

- They read the S1 and Flair Brain Image Series. A fused image series, denoted as F(x1, y1), is generated by combining the S1 and Flair Brain Image Series.

In order to remove the grayscale matter from the skull of the brain picture series F(x1,y1), it applies the skull strip.

Then obtained the combined MRI picture F(x1,y1)'s reflection brain image, r (x1,y1). The MRI image difference, or D(x1, y1), is obtained by deducting F(x1, y1) from r(x1, y1).

The formula for this is $D(x1, y1) = F(x1, y1) – r(x1, y1)$ (1)

- Subsequently, the image is segmented by edges or regions using the Advance Contour Method (ACM).
- Finally, employ the *imerode* and *imdilate* (MATLAB techniques) procedure frequently until the MRI brain tumor is removed for precise brain tumor isolation.

### 3.1.2 Active Contour-Based Segmentation-

- Active contour models, commonly referred to as snakes or deformable contours, are extensively utilized in image processing and computer vision for segmentation purposes.
- Given: Approximate Contour around the object
- Objective: Adjust the contour to match the precise object border.
- Active Contour: Gradually modify the basic contour to approach the pixel with a strong gradient (edges of the object).


Figure 6 Active Contour based segmentation.

For example, as shown in Figure 6, we need to segment the COIN portion from the given image. We apply the active contour-based segmentation technique, in which we start with an initial curve in the image. This contour can be user-defined or can be generated automatically. An energy function represents the image characteristics and desired properties of the contour. Usually, there are two parts to the energy function: internal energy and external energy. Internal energy enforces the smoothness of the contour and is related to its shape. The image provides external energy that draws the contour in the direction of object boundaries. We minimize the energy function by iteratively deforming the contour. This deformation is performed by solving a partial differential equation that governs the evolution of the contour.

We repeat the deformation process until the contour converges to the desired boundaries of the COIN.

The algorithm for the aforementioned segmentation technique is illustrated below.

**Algorithm for Active contour-based Based Segmentation**[28]

**Start**

Step 1. *Initialization:*

*Start with an initial curve or surface in the image.*

*This initial contour can be user-defined or generated automatically.*

Step *2. Energy Function:*

*Define an energy function that represents the image characteristics and desired properties of the contour.*

*Usually, there are two parts to the energy function: internal energy and external energy.*

*Internal energy enforces the smoothness of the contour and is related to its shape.*

*The image provides external energy that draws the contour in the direction of object boundaries.*

Step *3. Minimization:*

*Minimize the energy function by iteratively deforming the contour.*

*This deformation is performed by solving a partial differential equation that governs the evolution of the contour.*

Step *4. Convergence:*

*Repeat the deformation process until the contour converges to the desired object boundaries*

*End*

### 3.1.3 Feature Extraction

- **Dual-Tree Complex Wavelength Transform (DT CWT)**

The dual-tree complex wavelet transform, also known as the DT-CWT, is a relatively new development from the discrete wavelet transform, also known as the DWT. Characteristics that the DT-CWT possesses directionally selective and shift invariant capabilities[29].

- **Local Binary Pattern (LBP)**

One of the most helpful texture descriptors for images is called the Local Binary Pattern (LBP), and it is based on the value of the current pixel to determine the threshold for the pixels that are close by. LBP descriptors are able to effectively capture all of the grayscale contrast and local spatial patterns that are present in an image.

- **Grey Level Run Length Matrix (GLRLM)**

The run-length characteristics offer a directionally-assisted evaluation of the coarseness of the texture. At the same time, the GLRLM algorithm computes the spatial correlations between groups of pixels that have gray-level values comparable to one another. For classification purposes, it makes use of BPNN Classifiers.

- **Morphological Operation**

Apply the morphological features based on shape-based distinct properties that are taken from the early phase or stage of cancer segmented region and edge. These properties are: (i) Major Length and (ii) Minor Length; (iii) Eccentricity; (iv) Roundness and Equi. Distance (ED). Next, use a method based on Discrete Wavelet Transform (DWT), Local Binary Pattern (LBP), and Grey Level Run Length Matrix (GLRLM) to analyze the text features from the image-segmented brain tumor edge. The primary method is demonstrated below:

1. The DWT approach produces three wavelet LL, HL, LH, and HH sub-bands, of which three are supplied into the LBP method.

2. The outcome of the LBP technique is three Linear Binary Pattern method images, which are numbered into 8 bits to create 8-bit indexed Brain Tumor Images.

3. Currently, 11 features are evaluated in 4 directions, such as 0, 45, 90, and 135 degrees, using the GLRL technique. 44 characteristics (4*11) are evaluated for each LBP index brain image.

4. A total of 132 features are assessed and used to train the staked ensemble model because there are three index MRI images.

5. Neural networks make use of these features.

### 3.1.4 Classification

An artificial neural network (ANN) is a mathematical model made up of multiple highly interconnected processing components arranged in layers, shapes, and functionalities that mimic the structure of the human brain.

The ANN can be thought of as having learning capabilities because it naturally stores experimental knowledge and makes it accessible for use at a later time. Three layers made up the neural network used as the classifier needed for this investigation. Seven input components chosen from the seven feature vectors derived from the PCA's wavelet coefficients made up the first layer. There were four neurons in the buried layer. Both the normal and dysfunctional human brains were represented by a single neuron in the output layer.

- **Back Propagation NN**

Back-propagation (BP) technique is the most widely used training algorithm in classification issues and is also applied in this research. The literature has a thorough documentation of the back-propagation (BP) algorithm's specifics. To generate the intended mapping, the neural network has been trained to modify the connection weights and biases.

During the training phase, the network receives the feature vectors as input and modifies its weights and biases, among other variable parameters, to ascertain the correlation between the input patterns and outputs.

### 3.2 Brain Tumor Classification and Segmentation using DTCW Transform, Back Propagation Neural Network and Spatial Fuzzy C-Means Clustering (BPNN-SFCM)

In this method, for feature extraction, the Dual-Tree Complex Wavelet Transforms are used, for the Classification of tumors Back Propogaction Neural Network is used, and Speical C- Means Fuzzy clustering for the segmentation of tumors.

The following algorithm illustrates the steps for the BPNN-SFCM method.

**Algorithm – BPNN-SFCM Method**[30]

*Start*

*Step 1: Input - As input, MRI samples are provided.*

*Step 2: Preprocessing – Preprocessing is done on the image to enhance its quality and yield more accurate results in later stages. (Median Filter)*

*Step 3: Feature Extraction – Image features are extracted from preprocessed files using DTCWT.*

*Step 4: BPNN is trained and tested for classification of MRI images into normal or abnormal (Benign/Malignant) types*

*Step 5: In order to separate the tumor portion of the MRI picture, a Special C Means Clustering is utilized.*

*End*

**Output:** Segmented tumor image

The block diagram of the proposed model is represented in Figure 7

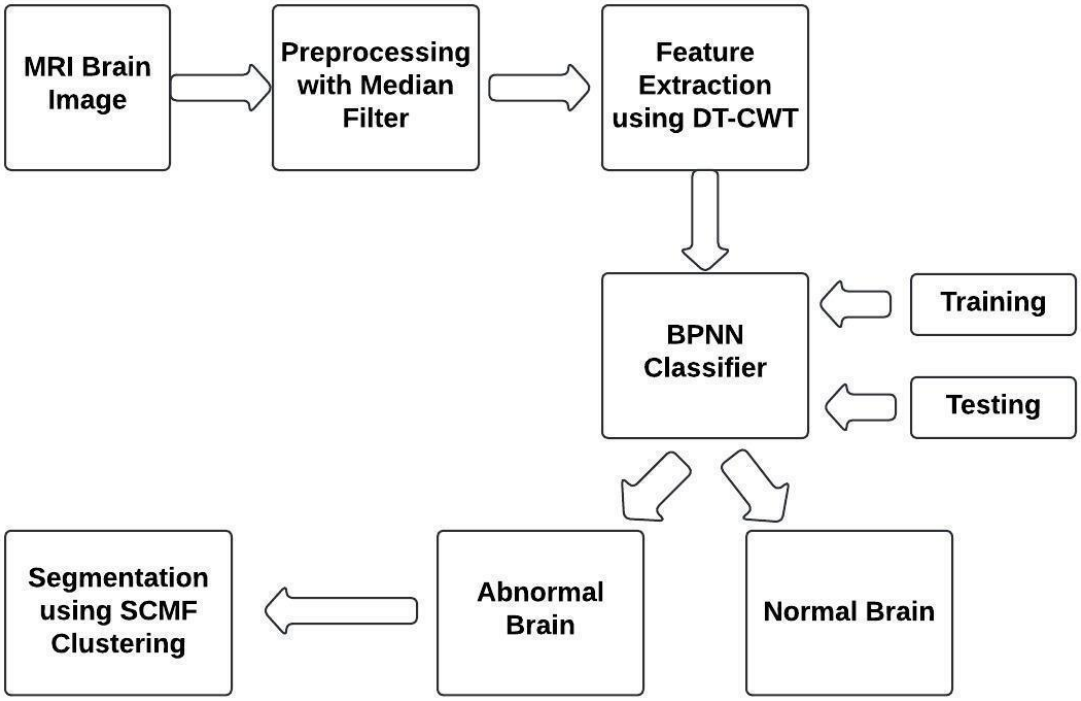



Figure 7 Block diagram of BPNN-SFCM method

### 3.2.1 Preprocessing

Preprocessing is done on the image to make it better and produce more accurate results in later stages. It is carried out in order to improve the work of subsequent processing and analysis. Creating a noiseless image is the initial step in this approach. The median filtering technique is used to remove impulsive noise in order to effectively detect brain tumors.

- **Median Filtering**[31]

The median filter is the filtering method used to remove noise from signals and images. Since the median filter is well known for maintaining edges during noise reduction, it plays a critical role in image processing.

The filter's primary responsibility is to scan all input data and replace all entries with the median function, sometimes called the "window" approach. Over the higher-dimensional signals, the window is typically a little more complex.

The number of medians, which fall into odd and even groups, is determined by the number of windows.

### 3.2.2 Feature Extraction Method

**a. Dual-Tree Complex Wavelet transforms (DTCWT)**

In order to identify the tumor in the brain MRI images, we need to extract the features from the outliers. This can be accomplished by using the feature extraction approach. In order to convert the dual-tree complicated wavelet-based function extract, the proposed approach and

eight distinct types of features are utilized. They are characteristics that are determined by the texture and intensity of the substance[32].

Dual-tree uses two true wavelet trees, each of which is capable of ideal reconstruction (PR). One tree produces the true component of the transform, and the additional tree is employed to construct the difficult section. A pair of exposed Quadrature Mirror Filters (QMF) in the real-coefficient assessment branch is denoted as $\{R_0(k), R_1(k)\}$. Another QMF pair in the research branch for the complex part is $\{J_0(k), J_1(k)\}$. The filters that support the Perfect Reconstruction (PR) criterion in DTCWT are referred to as linear phases. They are integrated to provide an analytical result for the transform.

$$\Psi(t) = \Psi_R(t)\ \Psi\ j\Psi_j(t) \quad (2)$$

The wavelet produced by two discrete wavelet transforms is represented by $\Psi R(t)$ and $\Psi j(t)$. Additionally, both low-pass filters $R_0(k)$ and $J_0(k)$ must possess a characteristic that allows them to create a coarse Hilbert transform pair with the corresponding wavelets.

$$\Psi_j(t) \cong H\{\Psi_R(t)\} \quad (3)$$

One of the two low-pass filters needs to have an approximately half-sample shift compared to the other for this reason.

$$J_0(k) \cong R_0(k\text{-}0.5) \rightarrow \Psi j(t) \cong H\{\Psi_R(t)\} \quad (4)$$

These half examples postpone fundamental ideas to facilitate consistent wavelet transformation.

The “Dual-Tree Complex Wavelet Transform (DTCWT)” possesses the following attributes:

- In two or more dimensions, it is nearly invariant to shifts and selectively directed.

- This is accomplished with a redundancy factor of only 2d for d-dimensional signals, significantly lower than the non-decimated “Discrete Wavelet Transform (DWT)”.

**b. Gray-Level Co-Occurrence Matrix (GLCM)**

The Grey Level Co-occurrence Matrix (GLCM) is a statistical technique utilized in image processing and computer vision to describe the spatial connections among pixel intensities in a digital image.

Analyzing the distribution of pixel pairings with specified intensity correlations provides information about the texture and patterns contained in an image.

i. Grey Level: Each pixel in digital photographs has a distinct intensity value, typically depicted in grayscale. "Grey level" pertains to intensity values.

ii. Co-occurrence: GLCM analyses the frequency of pairings of pixel intensities in relation to each other inside a picture.

iii. Matrix: The GLCM is depicted as a matrix, where each element (i, j) indicates the frequency of pixel pairs with intensities i and j at a specific spatial relationship.

The GLCM is computed by analyzing pixel pairs at a specific distance and orientation in the image. The process comprises the following steps:

i. Image Preparation: Transform the original image to grayscale if it is in color.

Pixel Pair Calculation: Analyze the neighboring pixel of each pixel in the image based on a defined distance and direction.

ii. GLCM Construction: Construct a matrix where each element (i, j) denotes the frequency of the pixel intensity pair (i, j) inside the defined spatial relationship.

iii. Normalization: Normalize the matrix by dividing each element by the total of all elements in the matrix to produce probabilities.

Through the utilization of the GLCM, several texture aspects such as contrast, correlation, energy, and homogeneity may be extracted, hence providing insights into the texture of the image as well as the spatial interactions between its elements. Image analysis, pattern recognition, and machine learning are all examples of applications that can benefit from these properties.

The Grey Level Co-occurrence Matrix is a technique that captures statistical characteristics of pixel intensity correlations in order to provide a quantitative description of the texture and patterns that are present in digital photographic images.

### 3.2.3 Classification

**a. "Back Propagation Network"**

The Backpropagation algorithm consists of four phases.

i. Feed-forward computation.

ii. Return to the output layer

iii. Return to the hidden layer

iv. Updating weights

The stepwise process is depicted in the below algorithm.

**Back Propagation Neural Network Algorithm**[33]

*Start*

*Step 1 - Initialization:*

*Initialize the weights and biases of the neural network with small random values.*

*Step 2 - Forward Pass:*

*Propagate the input data forward through the network to compute the predicted output.*

*Apply sigmoid activation functions in the hidden layers at each neuron to introduce non-linearity.*

$$S(x) = \frac{1}{1 + e^{-x}}$$

*Step 3 - Compute Loss:*

*Determine the discrepancy between the expected output and the real target output. Common loss functions for classification tasks include Mean Squared Error (MSE).*

$$MSE = \frac{1}{n}\sum_{i=1}^{n} (Y_I - Y_i)^2$$

*Step 4 - Backward Pass:*

*Backpropagate the fault through the network.*

*Calculate the gradient of the loss function in relation to the weights and biases of the neural network.*

*Step 5 - Adjust Weights:*

*Adjust the weights and biases in the network to minimize the error.*

*This is done using an optimization algorithm such as stochastic gradient descent (SGD)*

*Step 6 - Iterate:*

*Repeat the process of step 2,3,4,5 for a specified number of iterations (epochs) or until convergence.*

*Step 7 - Convergence Check:*

*Convergence occurs when the model's performance stabilizes or reaches a satisfactory level.*

*Step 8 - Testing:*

*Assess the generalisation performance of the training model by evaluating it on a distinct test dataset.*

*End*

The process will terminate automatically if the error function value is too low. The Figure 8 represents a three-layered network. [34].

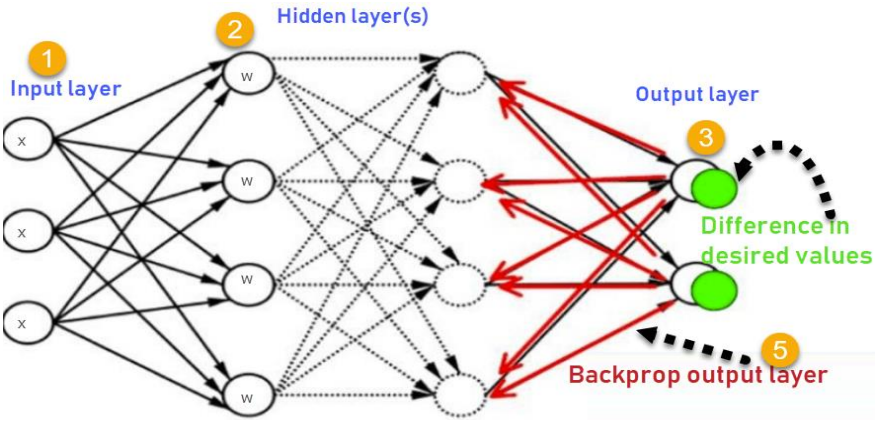



Figure 8 Back Propagation Neural Network

Advantages and disadvantages of BPNN network: -

- Training a BPNN is typically faster than training a multilayer perceptron network.
- BPN networks are typically more accurate than multi-layer perceptron networks.
- Outliers have minimal impact on BPN networks.
- BPN networks generate accurate target probability ratings.
- Networks using Bayesian probabilistic networks (BPN) aim to achieve optimal categorization based on Bayes' theorem.
- BPN networks exhibit slower classification of new cases compared to multilayer perceptron networks.

BPN models are larger than multilayer perceptron networks because each training line contains one neuron, which is a disadvantage of BPN models. The model will operate slower than multilayer perceptron networks when scoring to forecast values for new rows.

Removing superfluous neurons has three advantages:

- The saved model has been reduced in size.
- The time required to apply the model decreases during scoring.
- Removing neurons frequently enhances the model's precision.

An iterative strategy involves eliminating redundant neurons. Leave-one-out validation involves removing one neuron at a time to evaluate the model's error. The neuron with the lowest error rate (or potentially the highest error reduction) is then removed from the model. The process is repeated using the remaining neurons until the stop requirement is met.

Back Propagation Networks are utilized for addressing classification problems. The BPN classifier demonstrated good accuracy, quick training time, resilience to weight adjustments, and minimal retraining time.

### 3.2.4 Segmentation with Spatial Fuzzy C-Means Clustering

Fuzzy C-Means (FCM) is a clustering technique that expands upon the traditional K-Means algorithm by including fuzzy or probabilistic membership of data points to different groups [35]. This gives the technology the ability to classify data points into several clusters. It is very helpful to employ FCM in situations when there is uncertainty in allocating data points to a single cluster. This is something that frequently takes place when the boundaries between clusters are not clearly defined.

A spatial function is proposed to be incorporated into the membership function of the conventional fuzzy c-means approach. Through the process of assigning weights to neighboring pixels depending on their relationship with the central pixel in the surrounding window, the spatial function is able to maximize the spatial aspects of the image. FCM is particularly useful when there is ambiguity in assigning data points to a single cluster, which often occurs when the boundaries between clusters are not well-defined.

The spatial function maximizes the spatial features of the image by assigning weights to nearby pixels based on their relationship with the central pixel in the surrounding window. The process flow of fuzzy c-means is enumerated below:

**The algorithm for Spatial Fuzzy C Means Clustering**[36]

*Start*

*Step 1: Assume a fixed number of clusters k.*

*Step 2: Assign coefficients randomly to each data point for being in the clusters.*

*Step 3: Repeat until the algorithm has converged*

*a. Compute the centroid for each cluster.*

*b. For each data point, compute its coefficients of being in the clusters.*

*End*

*o/p - The final cluster centers and membership values represent the fuzzy partition of the data.*

## 4. Results and discussion

This section demonstrates the efficacy of the suggested models by testing them on a range of brain MRI images from the BRATS dataset. In this section, a detailed explanation of the datasets used in the analysis, the baseline methodologies that have been applied, the evaluation measures that have been taken, and the outcomes that have been produced are provided.

### 4.1 Datasets

In this section, the dataset that is required to examine various brain tumor detection, classification, and segmentation methods is described.

Experiments are carried out using the BRATS dataset. The description of the dataset is given below:

#### 4.1.1 BRATS[37], [38], [39]

Since 2012, the International Brain Tumor Segmentation (BraTS) competition has aimed to provide a standardized environment and dataset for accurately outlining adult brain gliomas. BraTS has always emphasized assessing cutting-edge techniques for segmenting brain tumors in multimodal magnetic resonance imaging (MRI) data. All BraTS multimodal scans are accessible in NIfTI file format (.nii.gz) and are detailed as follows:

a) native (T1)

b) post-contrast T1-weighted (T1Gd)

c) T2-weighted (T2), and

d) T2 Fluid Attenuated Inversion Recovery (T2-FLAIR) volumes

Images were obtained using diverse clinical protocols and scanners from 19 different institutions, which are identified as data sources. The specifics of the dataset utilized are displayed in Table 4.

Table 4 Images from the BRATS dataset

| **Type** | **Cancerous** | | **Non-Cancerous** |
|---|---|---|---|
| **Modalities** | **Testing images** | **Training images** | **Training images** |
| **flair** | 300 | 300 | 300 |
| **T1** | 300 | 300 | 300 |
| **T1Gd** | 300 | 300 | 300 |
| **T2** | 300 | 300 | 300 |
| **Total** | **1200** | **1200** | **1200** |

In this study, we trained, validated, and tested our pipeline using the BRATS dataset, which contains Multi-Modal MRI images and patient clinical data with varied heterogeneous histological sub-regions, varying degrees of aggressiveness, and variable prognoses.

In contrast to Computed Tomography (CT) images, these Multi-Modal MR images, which measure 240 by 240 by 150, were obtained clinically from many institutions utilizing diverse scanners, procedures, and magnetic field intensities.

We randomly separated the 3600 cases in this dataset into training data (66.33%) and test data (33.33%).

The dataset was gathered from https://www.med.upenn.edu/cbica/brats/, the website of the BRATS program. Figure 9 displays MRI images from the T1, T2, T1Gd, and Flair groups.

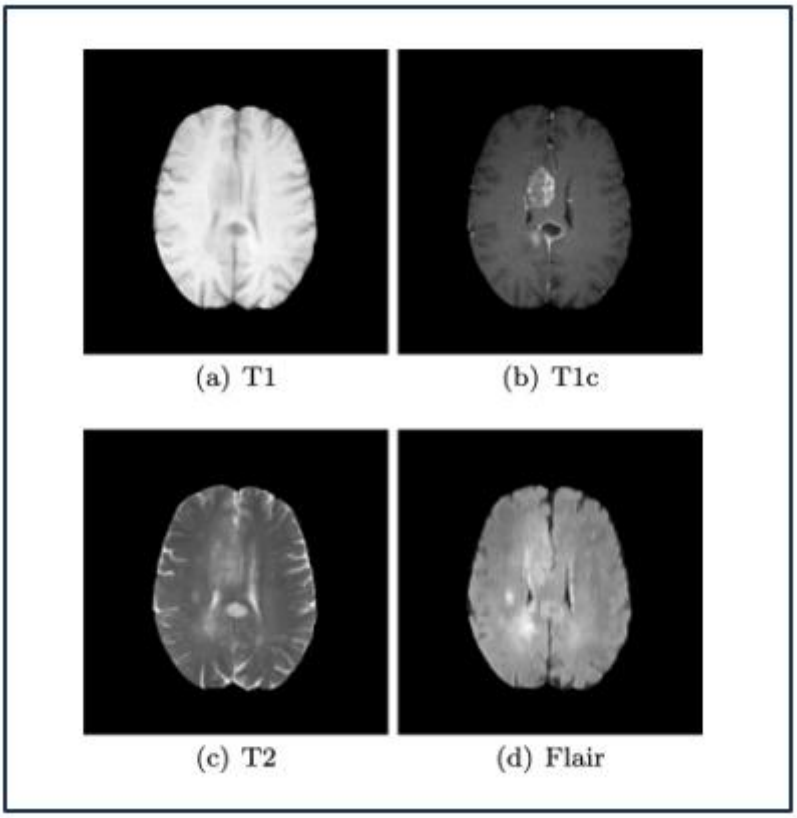



Figure 9 MRI Brain Dataset Images

### 4.2 Evaluation Metrics

In this section, we outlined our evaluation technique that sets the standards for determining the success of the research.

First, we describe in detail how the recognition accuracy of our system will be measured, with specific reference to several of the most prevalent performance indicators used in brain tumor detection, classification, and segmentation.

The performance metrics of the suggested models are described in the following section, which are being evaluated and verified.

- Patient = Afflicted with disease
- Healthy = Free from disease
- True positive (TP) = The number of accurately recognized patient instances
- False positive (FP) = Number of wrongly identified patient cases
- True negative (TN) = Number of accurately identified healthy cases
- False negative (FN)= Refers to the instances where cases are mistakenly classified as healthy.

- **Sensitivity-** Sensitivity refers to the capability of a test to identify those with the disease correctly. This can be expressed mathematically as:

$$sensitivity = \frac{True\ Positive}{True\ Positive + False\ Negative} * 100 \quad (5)$$

- **Specificity:** Specificity refers to the capability of a test to identify those without the disease correctly. This can be expressed mathematically as:

$$Specificity = \frac{True\ Negative}{True\ Negative + False\ Positive} * 100 \quad (6)$$

- **Accuracy:** Test accuracy refers to its capacity to correctly distinguish between patients and healthy individuals. Mathematically, this can be expressed as:

$$Accuracy = \frac{True\ Negative + True\ Posiive}{True\ Positive + False\ Positive + True\ Negative + Fasle\ Negative} \quad (7)$$

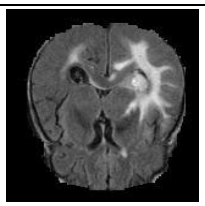
**Experimental Results for MONN Method**[40]

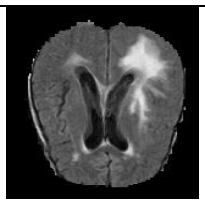
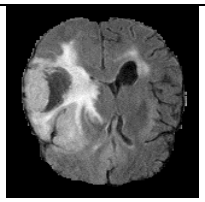
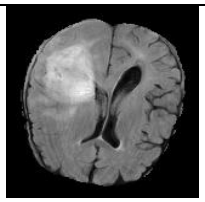
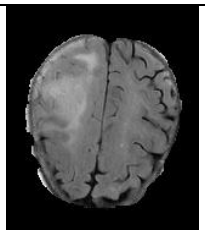
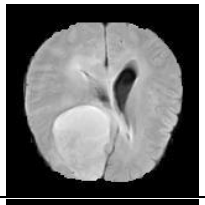
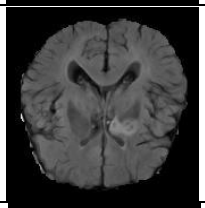
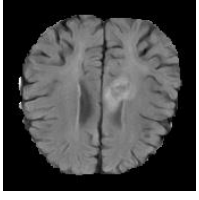
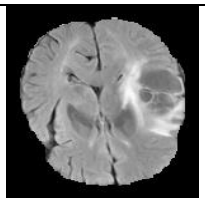
The experimentation was carried out on BRATS datasets, entailing the pre-processing of input brain MRI images to eliminate noise through the application of a Median Filter. Subsequently, features were extracted from sample images utilizing Discrete Wavelet Transforms, Local Binary Patterns, and Gray Level Run Length Matrix methods. These extracted features served as input for the Back Propagation Neural Network (BPNN) classifier. The detailed outcomes of the BPNN classifier are presented comprehensively in the ensuing table.

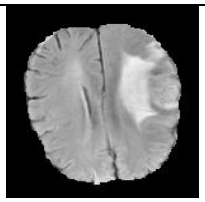
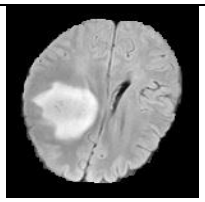
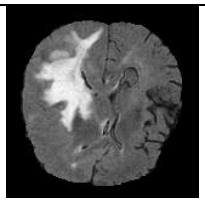
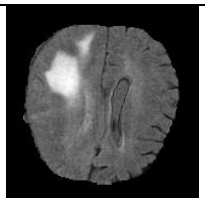
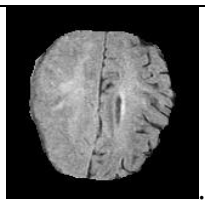
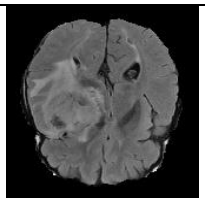
To refine tumor segmentation, an Advanced Active Contour-based segmentation method was employed. This sophisticated approach enhances the precision and accuracy of segmenting tumor regions within brain images. The effectiveness of the proposed methodology is meticulously documented in Table 5, which provides a comprehensive quantitative assessment of its performance metrics.

Furthermore, the results are visually illustrated in Figure 10, offering a graphical representation that facilitates a more intuitive understanding of the method's efficacy in brain tumor classification and segmentation. This dual presentation of data ensures both statistical rigor and visual clarity, underscoring the robustness of the segmentation technique.

Table 5 Performance analysis of MONN model on various test samples

| Test Image | Input Image | Normal/ Abnormal | Accuracy | Sensitivity | Specificity |
|---|---|---|---|---|---|
| Test image 1 |  | Abnormal | 98.31% | 100.00% | 96.67% |

| | | | | | |
|---|---|---|---|---|---|
| Test image 2 |  | Abnormal | 9132% | 93.55% | 96.43% |
| Test image 3 |  | Abnormal | 9132% | 96.55% | 93.33% |
| Test image 4 |  | Abnormal | 91.53% | 96.30% | 87.50% |
| Test image 5 |  | Abnormal | 88.14% | 8125% | 92.31% |
| Test image 6 |  | Abnormal | 93.22% | 96.43% | 90.32% |
| Test image 7 |  | Abnormal | 91.53% | 96.30% | 87.50% |
| Test image 8 |  | Abnormal | 92.46% | 96.25% | 93.26% |
| Test image 9 |  | Abnormal | 95.65% | 97.32% | 95.41% |

| | | | | | |
|---|---|---|---|---|---|
| Test image 10 |  | Abnormal | 92.49% | 96.52% | 93.49% |
| Test image 11 |  | Abnormal | 93.19% | 96.33% | 96.25% |
| Test image 12 |  | Abnormal | 94.23% | 97.15% | 97.52% |
| Test image 13 |  | Abnormal | 92.76% | 95.25% | 93.25% |
| Test image 14 |  | Abnormal | 91.94% | 96.24% | 94.46% |
| Test image 15 |  | Abnormal | 93.31% | 94.25% | 95.24% |

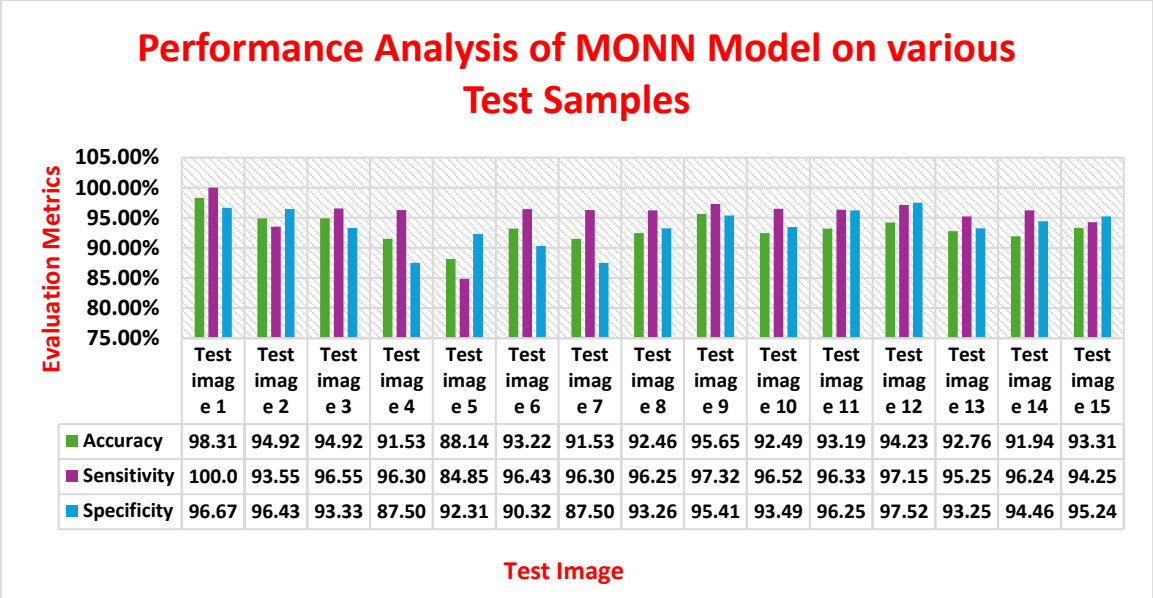



Figure 10 Visual Representation of performance analysis of MONN model

The overall performance of the MONN model is comprehensively detailed in Table 4.6 and is visually represented in Figure 11. These presentations collectively highlight the model's capabilities in segmentation and classification of brain tumors. Table 6 provides a thorough analysis of the model's performance metrics, while the graphical depiction in Figure 11 offers a clear visual interpretation of these results. Together, these elements underscore the robustness and suitability of the MONN model for accurately segmenting and classifying brain tumors, demonstrating its potential as a reliable tool in medical image analysis.

Table 6 Overall Performance of MONN Method

| Evaluation Metrics | Result in % |
|---|---|
| **Accuracy** | 96.61% |
| **Sensitivity** | 96.66% |
| **Specificity** | 96.55% |

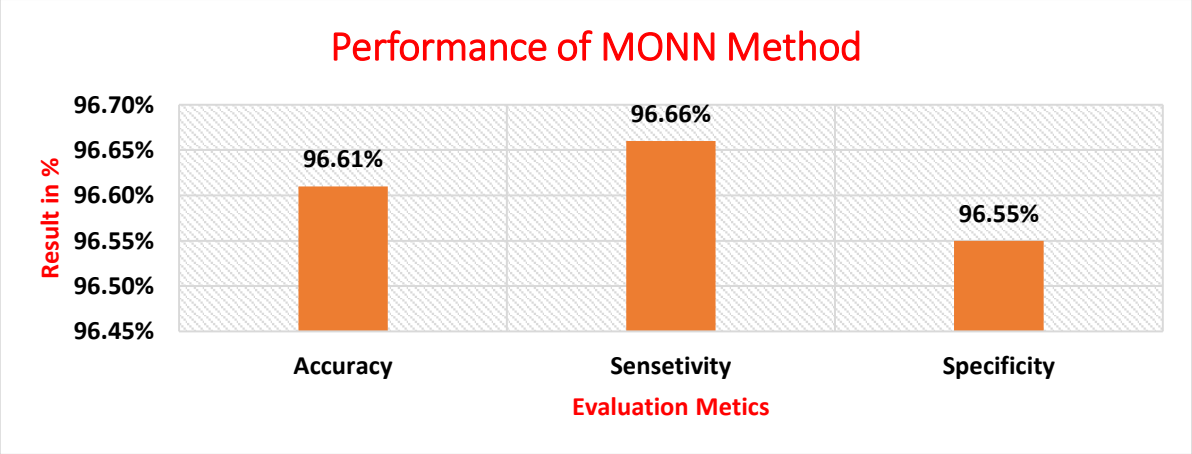



Figure 11 Overall Performance of MONN Method

**Interpretation:**

The Proposed method attained an accuracy rate of 96.91%, a Sensitivity of 96.66%, and a Specificity value is 96.55%. This achievement highlights the method's robustness and suitability for its intended application.

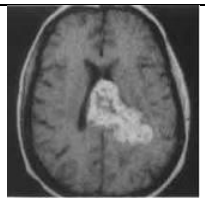
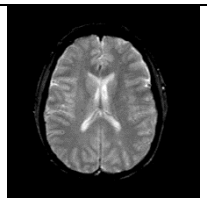
### 4.4.3 Experimental Results for BPNN-SFCM Method[41]

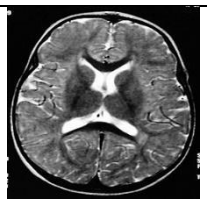
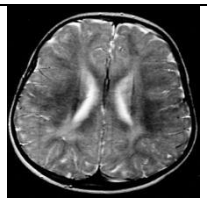
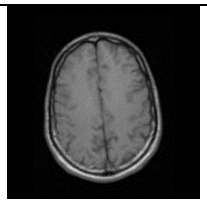
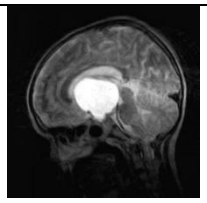
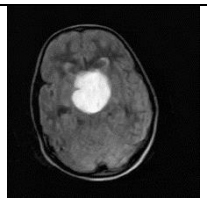
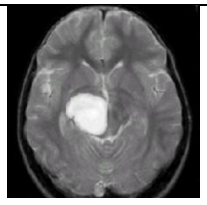
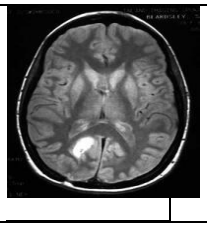
The experimentation involved the utilization of BRATS datasets. In this comprehensive study, brain MRI images were subjected to preprocessing techniques, specifically noise removal using a Median Filter. Subsequently, features were meticulously extracted from sample images utilizing the sophisticated Dual-Tree Complex Wavelength Transform.

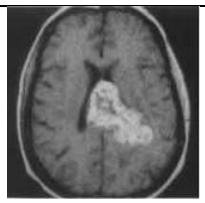
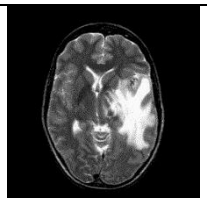
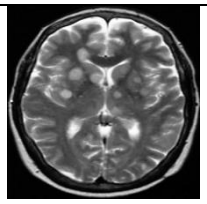
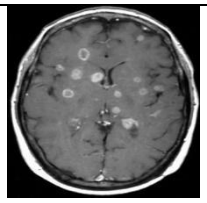
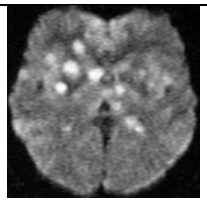
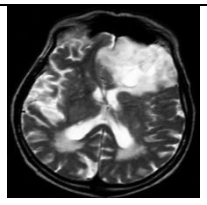
These extracted features were then fed into the Back Propagation Neural Network (BPNN) classifier for further analysis. The outcomes of the BPNN classifier, including various performance metrics, are meticulously presented in the subsequent table. Moreover, to delineate the tumor region, a Special C Means Fuzzy Clustering method was employed, providing a refined segmentation of the tumor within the images.

The accuracy of the proposed methodology is meticulously documented in Table 7 and graphically represented in Figure 12. This dual reporting approach offers a comprehensive understanding of the model's performance, combining numerical precision with graphical insight for a thorough assessment.

Table 7 Performance evaluation of BPNN-SFCM Method

| **Test Image** | **Input Image** | **Normal/ Abnormal** | **Accuracy** | **Sensitivity** | **Specificity** |
|---|---|---|---|---|---|
| Test Image 1 |  | Abnormal | 97.8439 | 91.49113 | 99.1007 |
| Test Image 2 |  | Normal | 100 | 100 | 100 |

| | | | | | |
|---|---|---|---|---|---|
| Test Image 3 |  | Normal | 100 | 100 | 100 |
| Test Image 4 |  | Normal | 100 | 100 | 100 |
| Test Image 5 |  | Normal | 100 | 100 | 100 |
| Test Image 6 |  | Abnormal | 99.768 | 98.6945 | 99.87575 |
| Test Image 7 |  | Abnormal | 99.8779 | 98.5924 | 99.94078 |
| Test Image 8 |  | Abnormal | 100 | 100 | 100 |
| Test Image 9 |  | Abnormal | 98.2955 | 94.2879 | 99.02438 |

| | | | | | |
|---|---|---|---|---|---|
| Test Image 10 |  | Abnormal | 97.8439 | 91.49113 | 99.1007 |
| Test Image 11 |  | Abnormal | 81.8222 | 41.84069 | 86.3781 |
| Test Image 12 |  | Abnormal | 100 | 100 | 100 |
| Test Image 13 |  | Abnormal | 100 | 100 | 100 |
| Test Image 14 |  | Abnormal | 100 | 100 | 100 |
| Test Image 15 |  | Abnormal | 100 | 100 | 100 |

The performance of the method is visually represented in Figure 12, which facilitates a more intuitive understanding of the method's efficacy in brain tumor classification and segmentation. This visual representation helps to clearly express the strengths and effectiveness of the method by illustrating key performance metrics such as accuracy, sensitivity and specificity.

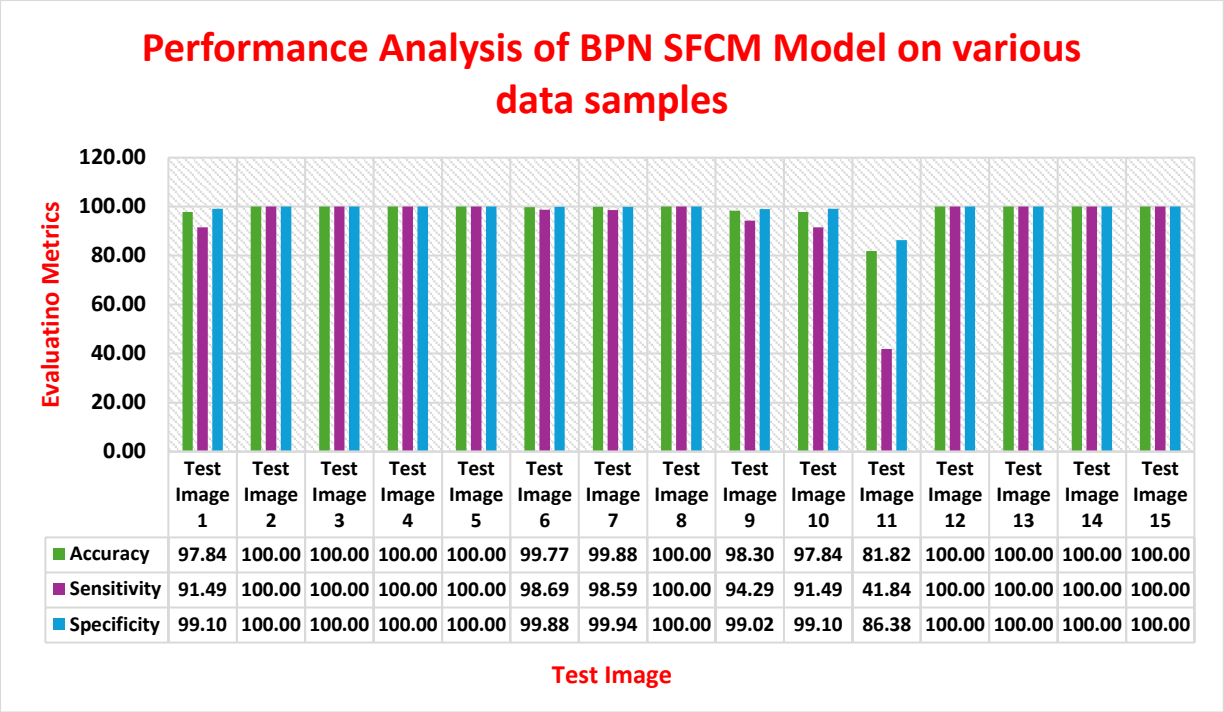



Figure 12 Visual Representation of performance analysis of BPNN-SFCM model

The overall performance of the BPNN-SFCM model is thoroughly presented in Table 8 and visually illustrated in Figure 13 These presentations offer a detailed evaluation of the model's capabilities in detecting, classifying, and segmenting brain tumors in MRI images. Table 8 provides an in-depth quantitative analysis of the model's performance metrics, including accuracy, precision, recall, and other relevant statistics. Figure 13 enhances this information with a visual depiction, facilitating a more intuitive grasp of the model's effectiveness. Together, these elements highlight the model's robustness and reliability in processing MRI images for the accurate identification and segmentation of brain tumors, emphasizing its potential as a valuable tool in medical imaging and diagnostics.

Table 8 Overall Performance of BPNN-SFCM Method

| Evaluation Metrics | Result in % |
|---|---|
| **Accuracy** | 99.77% |
| **Sensitivity** | 98.69% |
| **Specificity** | 99.87% |

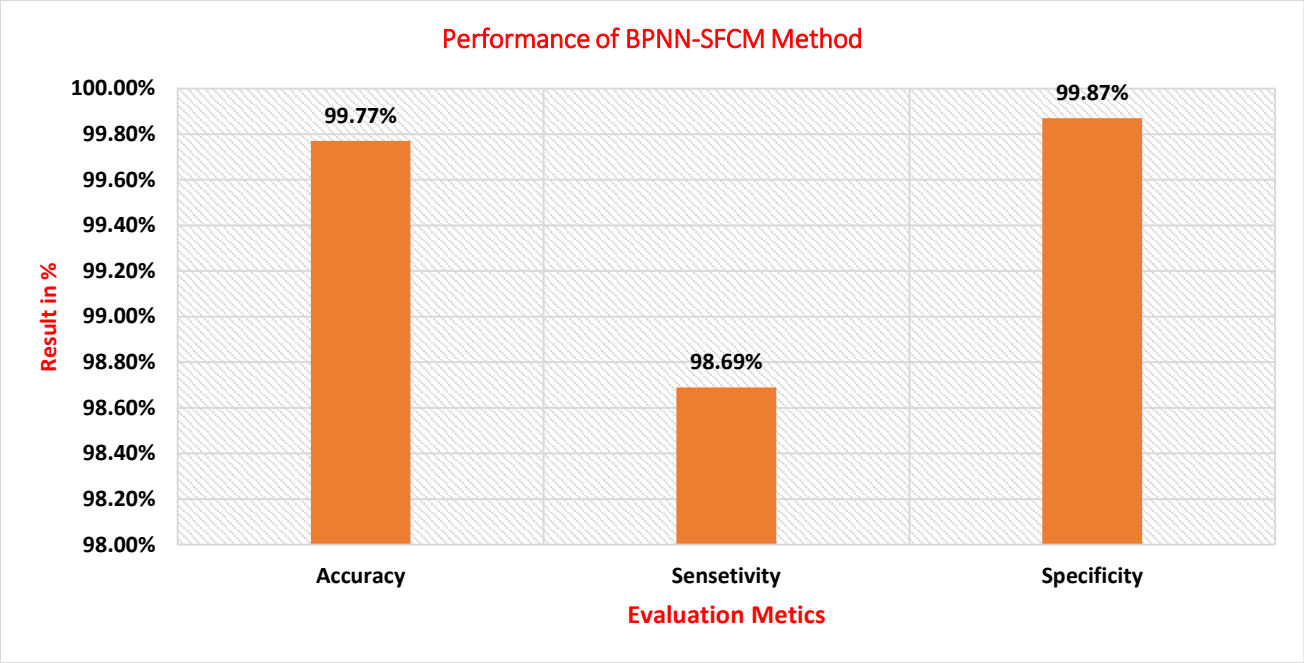



Figure 13 Overall Performance of BPNN-SFCM Method

**Interpretation:**

The BPNN-SFCM method demonstrates enhanced performance, as evidenced by the achieved results.

The method attains a commendable accuracy rate of 99.77%, it exhibits a Sensitivity rate of 98.69%, indicating its effectiveness in correctly identifying positive instances, and a specificity rate of 99.87%, underscoring its ability to accurately recognize negative instances.

**Overall Comparison of Proposed Methods and Existing Methods**

The proposed BPNN-SFCM, BW-DCNN, and MONN methods are compared with existing methods to show their effectiveness in the classification and segmentation of brain tumor MR images. Table 9 depicts a comparison of the proposed and existing method, and which is visually represented in Figure 14.

Table 9 Overall Comparison of proposed methods with existing methods

| **Method/Metrics** | **Accuracy** | **Sensitivity** | **Specificity** |
|---|---|---|---|
| **F2FCNN** [42] | NA | 89.00% | NA |
| **SVM** [43] | 81.42% | 80.00% | 83.33% |
| **Random Forest** [43] | 86.66% | 84.00% | 85.86% |
| **Mesh-Free Super-Diffusive Model** [44] | NA | NA | 90% |
| **KNN K-Means** [45] | 85% | 86.84% | 50.67% |
| **KNN** [46] | 84% | 86% | 88% |

| | | | |
|---|---|---|---|
| **Sparse Constrained Level Set Algorithm** [47] | NA | 96.03% | NA |
| **Deep Learning and Fuzzy K Means Clustering** [48] | 94.00% | 98.00% | 99.00% |
| **DL**[49] | NA | 86.00% | 91.00% |
| **Wavelet-SVM** [50] | 98.91% | NA | NA |
| **CNN MKKMC** [51] | 98.55% | 95.00% | 98.70% |
| **Hybrid Method** [52] | 97.70% | NA | NA |
| **DLRF** [53] | 97.80% | NA | NA |
| **MONN(Proposed Method)** | 96.61% | 96.66% | 96.55% |
| **BPNN-SFCM(Proposed Method)** | **99.77%** | **98.69%** | **99.87%** |

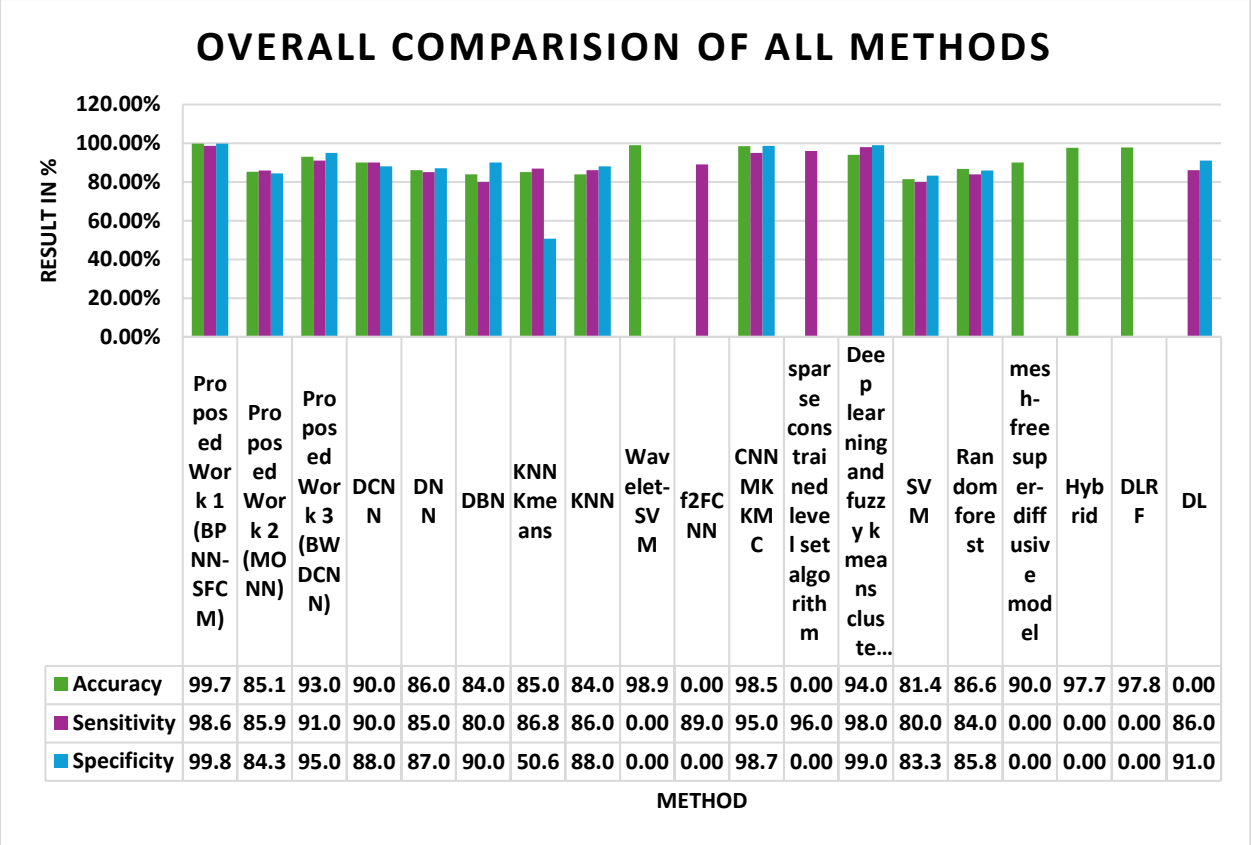



Figure 14 Overall Comparison of proposed methods with existing methods

**Interpretation:**

The experimental findings demonstrate that the Accuracy, Specificity, and Sensitivity achieved by the BPNN-SFCM approach are 99.77%, 99.87%, and 98.69% correspondingly, which surpasses other existing methods. BPNN-SFCM demonstrated superior performance compared to traditional approaches in extracting features optimally and classifying and segmenting brain tumors effectively.

After studying Figure 14, it is determined that the suggested approach BPNN-SFCM effectively classifies and segments brain tumors from MRI images when compared to other advanced methods.

## CONCLUSION

In medical imaging analysis, particularly in detecting, classifying, and segmenting brain tumors, we proposed three novel methods for automatic detection, classification, and segmentation of brain tumors in this research.

The FIRST approach defined a technique for classifying cancer and non-cancer MRI pictures. Firstly, MRI images are read by the classification system, and the fusion of multiple imaging modalities, such as Flair, T1, T1C, and T2 images, using a new wavelength coefficient maximum rule-based fusion method has been done to harness complementary information and improve the accuracy of tumor characterization. Then MRI image brain preprocessing and extraction of the features and classification is completed. In this preprocessing phase, Grayscale conversion, binarization, wavelet, and region of interest are calculated. After that, the research worked with the NN classification method with an effective method to classify the cancer and non-cancer brain images. The accuracy rate, specificity, and sensitivity of each layer in the classification scheme are evaluated to determine their performance. The results indicated that the research system outperformed alternative methodologies. Experimental analysis showed that the research method attained a classification accuracy of 96.61%, sensitivity of 96.66%, and specificity of 96.55%.

The SECOND approach combines Back Propagation Neural Network and Special Fuzzy C Means clustering. The backpropagation neural network is utilized to classify brains as normal, benignly abnormal, or malignantly abnormal. Spatial fuzzy C-means clustering is employed by segmentation for tumor localization and size determination in MRI images. We utilize a dual-tree complex wavelet transform to efficiently extract features from brain MRI images. After multiple experiments, we achieved a classification accuracy of 99.77% with a specificity rate of 98.69% and a sensitivity rate of 99.87%. The approach has demonstrated a accuracy of over 99% in extracting characteristics and classifying brain tumors effectively.

The overall analysis of the results of our experiments shows that our third method, BPNN-SFCM, is effective at enhancing, segmenting, and extracting brain tumors from MR images.

### *Future Work*

Future studies will focus on developing advanced algorithms that can effectively fuse information from multiple modalities, offering a more holistic understanding of tumor characteristics and improving segmentation accuracy.

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